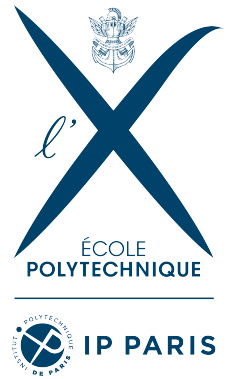
Reinforcement Learning I

INF581 Advanced Machine Learning and Autonomous Agents

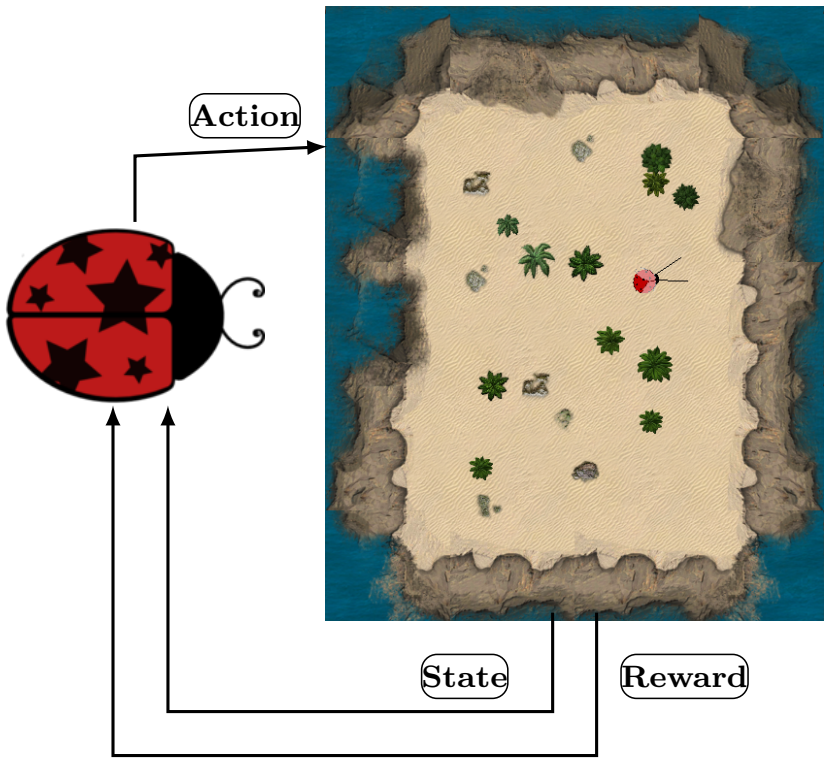
Jesse Read



Last Updated: January 26, 2022

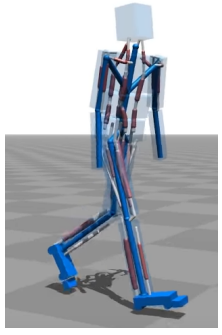
Introduction: Reinforcement Learning

- We are not given a data set; rather an environment
- No training labels; only reward signal
- Sequential decision making (non-i.i.d. data)
- The model is an agent; map state-observations to actions
- Main challenge: Reward signal is delayed, sparse, and/or weak

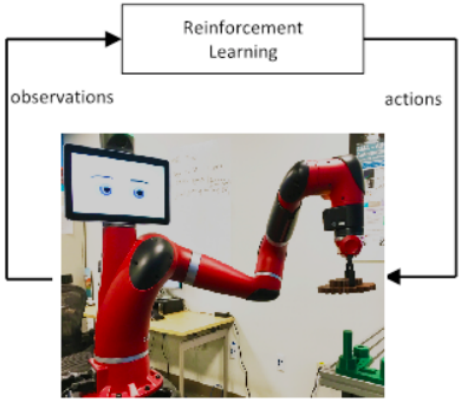


Introduction: Applications and Main Concepts

Applications: Fun and Robots

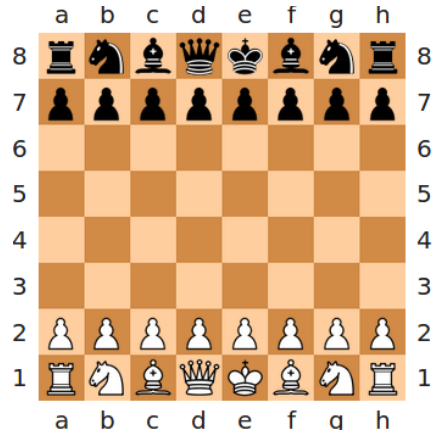


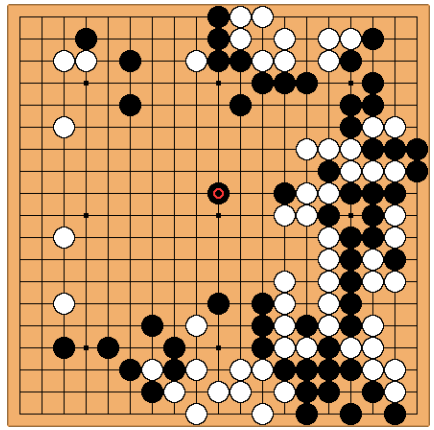
▸ AIGym ▸ Walker1 ▸ Walker2 ▸ Cars

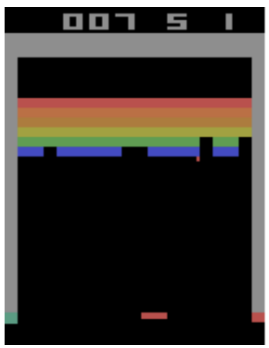


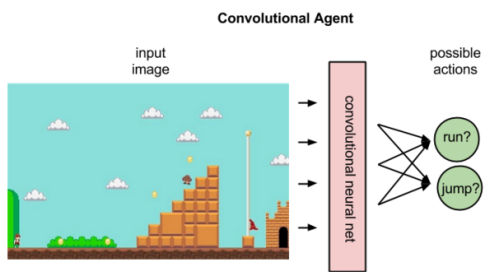
▸ Helicopter ▸ Robot ▸ More Robots

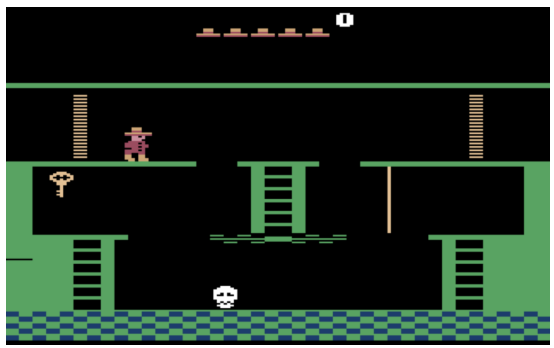
Applications: Games

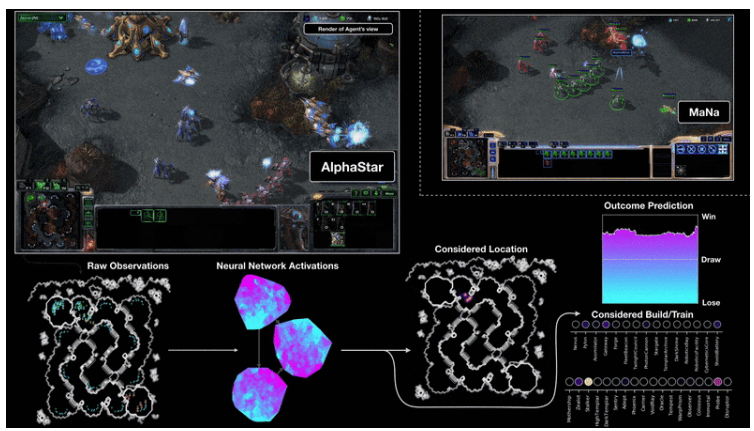








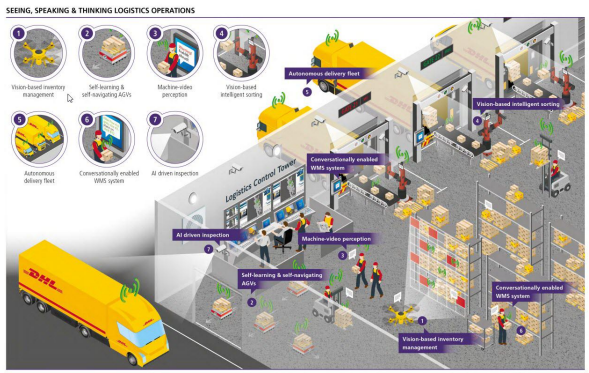


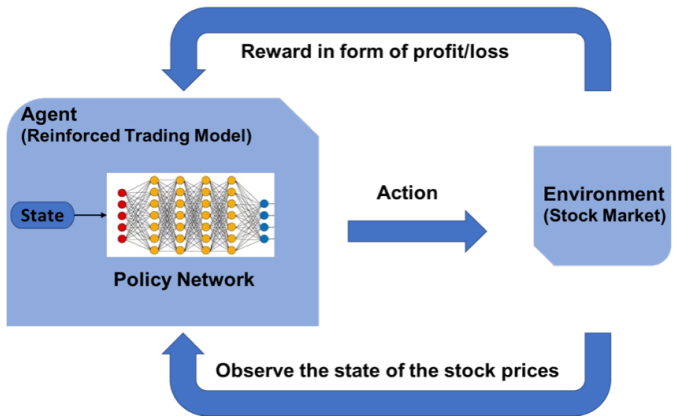


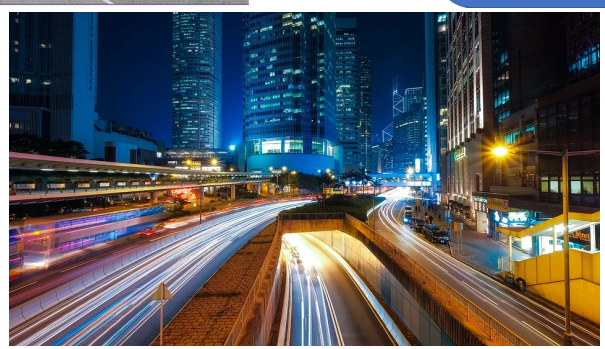
▸ FPS-Quake ▸ Starcraft-AlphaStar

Applications: Finance and Business

- Logistics; supply and demand (products, energy, . . .) ▸ Energy
- Trading/finance/manage investment portfolio ▸ IBM
- In recommendation engines, email advertising
- Marketing and advertising; real-time bidding ▸ Advertising/Bidding ▸ Bidding

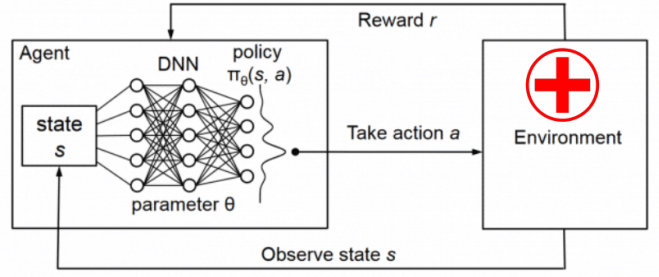






Applications: Education, Healthcare, Agriculture, . . .

- Healthcare: Diagnosis, manage hospital resources, . . . ▸ Health
- Education: Personalised/auto-generated curriculum, . . .
- Farming and Agriculture: Managing resources, . . .
- Sports
- Politics: Obtaining a policy ▸ Politics

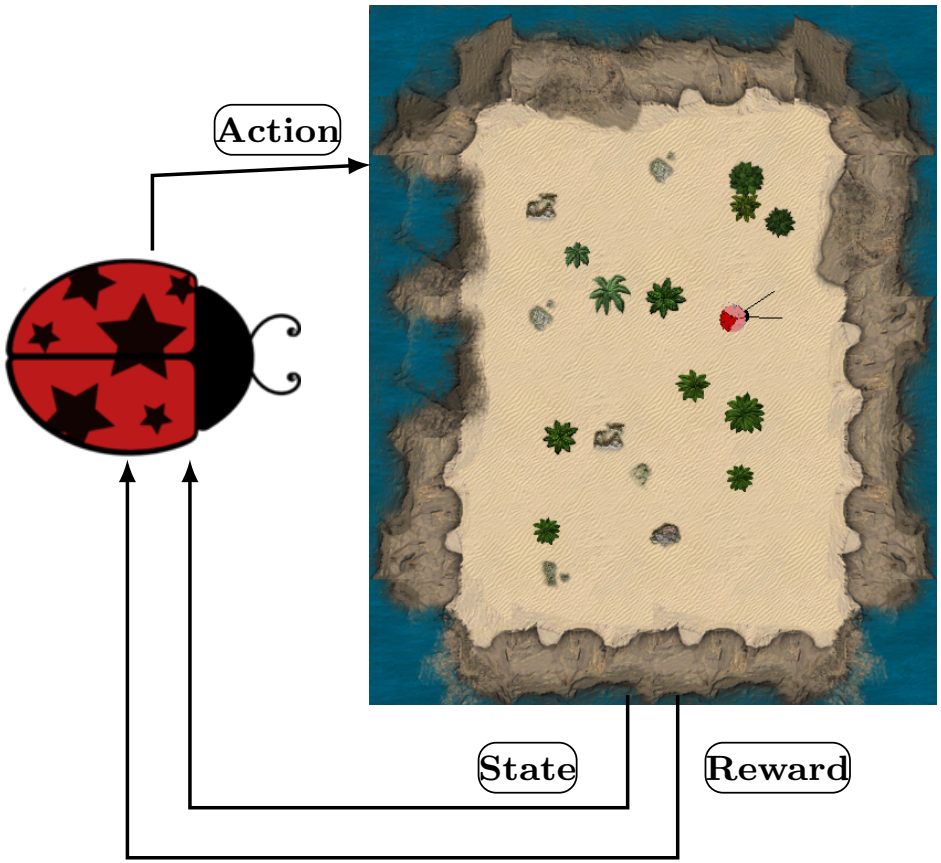


In NLP and Machine Learning

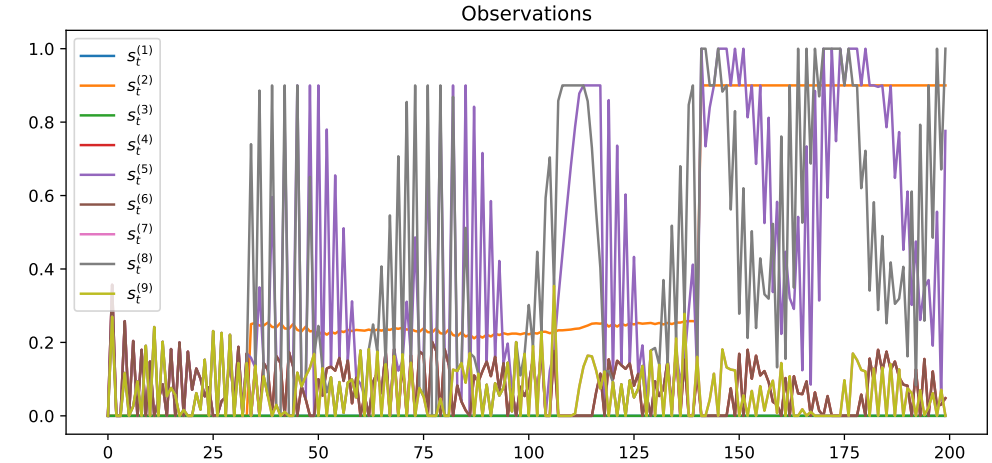
- Auto-tune the parameters of a deep neural network
- In chatbots
- In machine translation

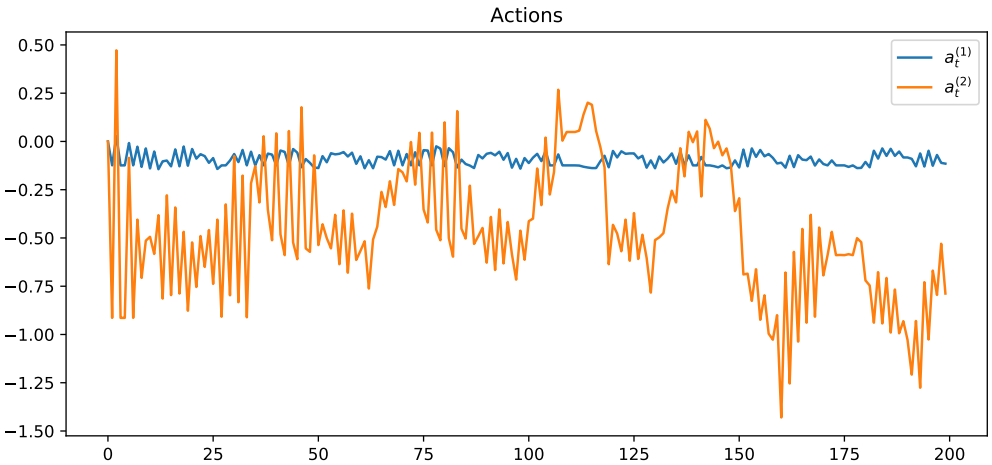
Number of real-world applications of reinforcement learning is increasing rapidly.

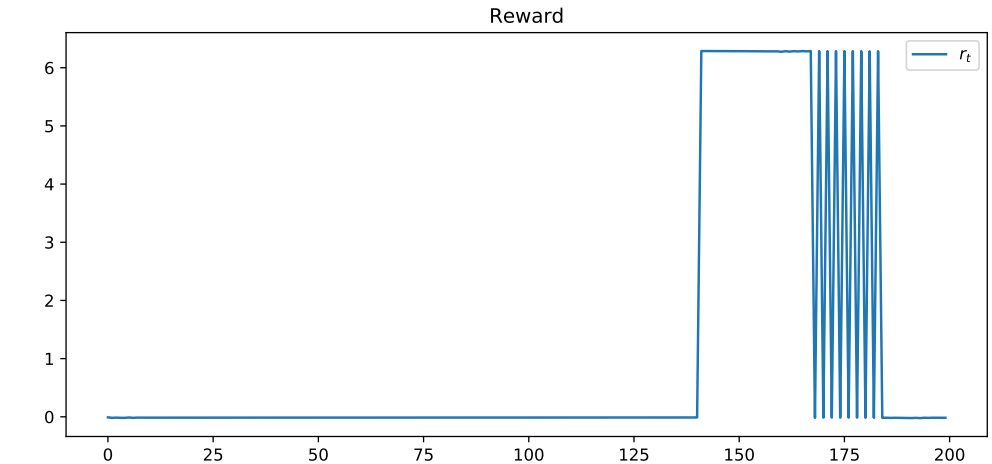
The Agent and the Environment



1. Observe the state of the environment
2. Obtain reward
3. Goal: select action to maximize future rewards.


Observations
$s_t^{(1)}$
$s_t^{(2)}$
$s_t^{(3)}$
$s_t^{(4)}$
$s_t^{(5)}$
$s_t^{(6)}$
$s_t^{(7)}$
$s_t^{(8)}$
$s_t^{(9)}$
1.0
0.8
0.6
0.4
0.2
0.0
0
25
50
75
100
125
150
175
200


Actions
$a_t^{(1)}$
$a_t^{(2)}$
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
−1.50
0
25
50
75
100
125
150
175
200


Reward
r_t
6
5
4
3
2
1
0
0
25
50
75
100
125
150
175
200

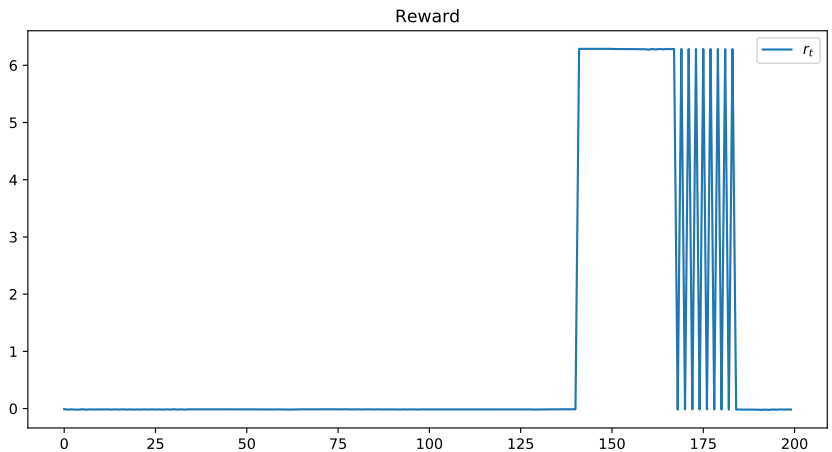
The Reward Signal

At time t we observe s_t, take action a_t, and obtain reward r_{t+1}. Over an episode, we see

$$s_1, a_1, \quad r_2, s_2, a_2, \quad r_3, s_3, a_3, \quad \ldots \quad , r_T, s_T$$

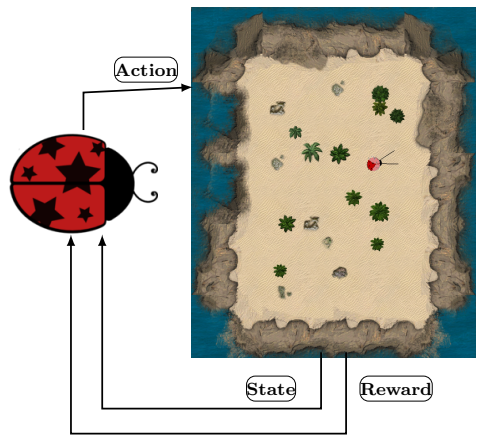
Problems:

- Reward signal is sparse: $r_t = 0$ or $r_t = -1$ most of the time
- . . . or weak: limited impact of best/worst actions on reward
- The temporal credit assignment problem: r_{t+1} may not be a result of a_t in any way; so which actions led to reward r_t?



Setting up the problem

- $\mathcal{S}$ state space, $s_t \in \mathcal{S}$
- $\mathcal{A}$ action space, $a_t \in \mathcal{A}$
- r reward function, $r_t = r(s_t, a_t)$
- p transition function, $s_{t+1} \sim p(\cdot|s_t, a_t)$



While s_t is not final:

1. $s_t, r_t \leftarrow \texttt{Env.step}(a_{t-1})$ ▷ Act upon environment; observe
2. $a_t \leftarrow \pi(s_t)$ ▷ Decide on an action
3. $t \leftarrow t + 1$ ▷ Continue

where $\pi : \mathcal{S} \mapsto \mathcal{A}$ is our policy.

The Policy

The policy defines the behaviour of the agent:

$$a_t = \pi(s_t)$$

indicates the action to take given the observation of the current state; i.e., the agent observes s_t and takes action a_t.

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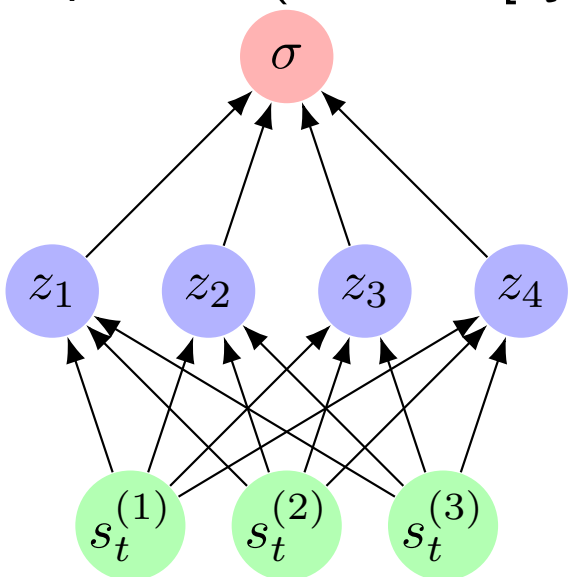
Example policies (let $s_t = [s_t^{(1)}, s_t^{(2)}, s_t^{(3)}]$, $a_t \in \{-1, +1\}$):



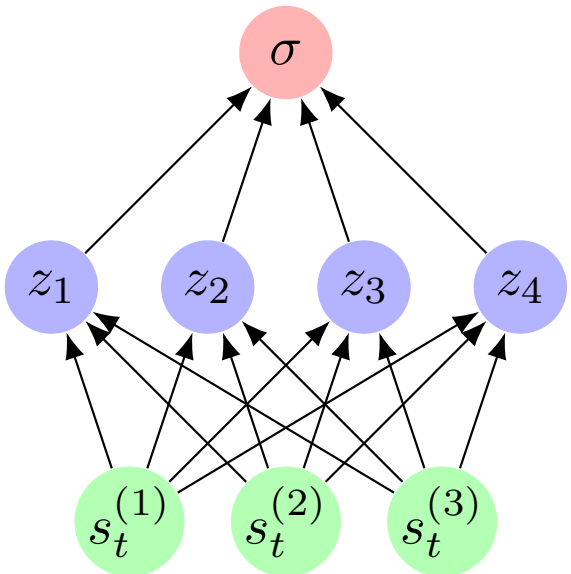
State s_1, s_2, s_3	Action a_t
0,1,0	-1
1,1,0	-1
0,1,1	+1
...	...

A policy can be any kind of mapping from states to action, e.g., via neural network, lookup (Q-)table, set of rules.

Stochastic Policy

A stochastic policy, where π provides a conditional probability distribution over actions given current state, and

$$a_t \sim \pi(\cdot|s_t) \quad \text{where } \pi(s_t) \in [0, 1]$$



State s_1, s_2, s_3	$\pi(-1\|s_t)$ σ	$\pi(+1\|s_t)$ $1-\sigma$
0,1,0	0.1	0.9
1,1,0	0.5	0.5
0,1,1	1	0
...	...	...

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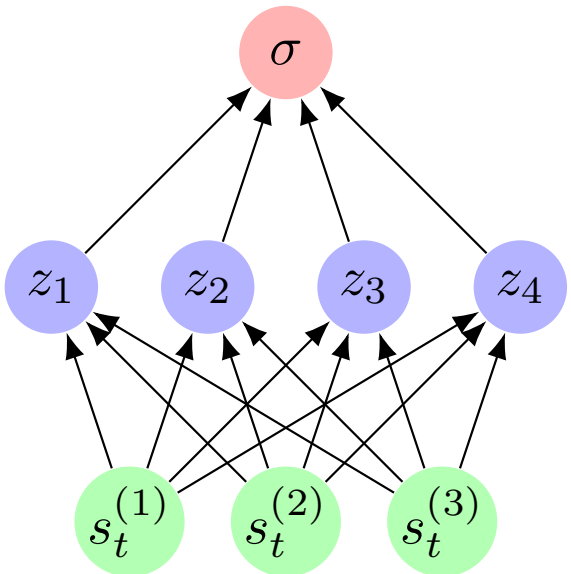

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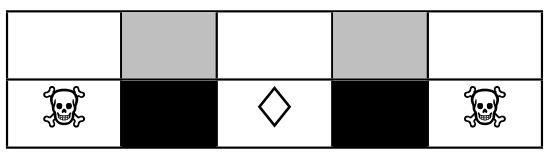
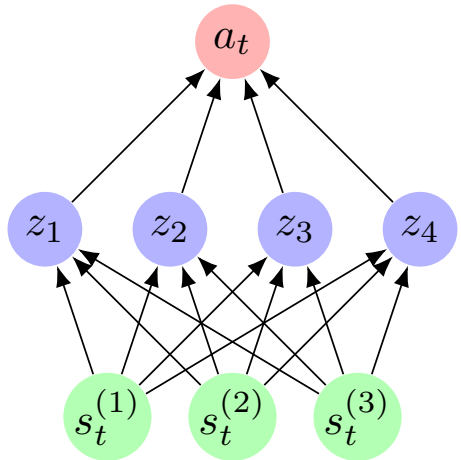
0,1,0	0.1	0.9
1,1,0	0.5	0.5
0,1,1	1	0
...	...	...

- Built-in exploration
- In competitive games, easier to defeat deterministic agents
- Aliased states: States that appear the same, but are not



Policy Search

Direct Policy Search (Black Box Optimization)



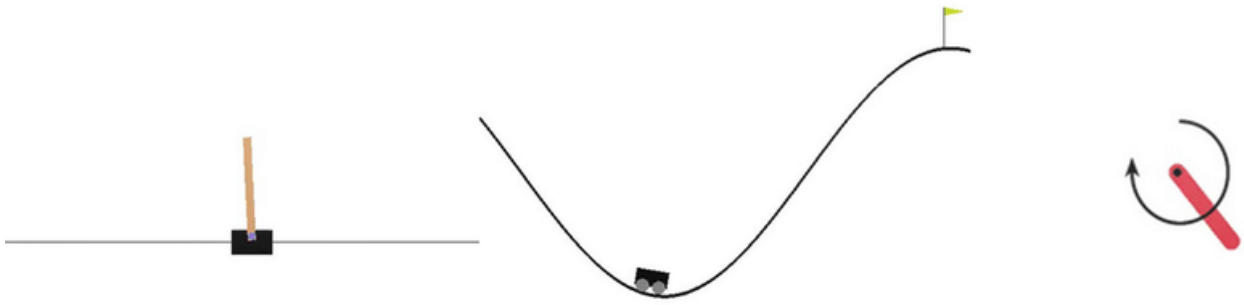
Suppose a parametric policy, parameters θ (e.g., of a neural network agent); i.e.,

$$a_t = \pi_\theta(s_t)$$

we can search directly in parameter space, i.e., policy search:

$$\theta^* = \underset{\theta \in \Theta}{\text{argmax}}\, g(\theta)$$

where $g(\theta)$ indicates how good π_θ is, e.g., $g(\theta) = 10 \Leftrightarrow$ agent survived 10 seconds / obtained score of 10 at end of episode.



- Many off-the-shelf search & optimization tools are available
- Works 'embarrassingly well' on some problems
- Handles continuous state/action spaces naturally
- No need to study reinforcement learning

But

- Expensive to evaluate $g(\theta)$ (run simulations/play games)
- Noisy (large $\mathbb{V}[g(\theta)]$); randomness from the environment!
- Curse of dimensionality: optimization in high dimensions (> 100) is very hard – it's why we don't train classifiers with black-box optimization!

Fully Observed Deterministic Environments

Fully Observed Deterministic Environments

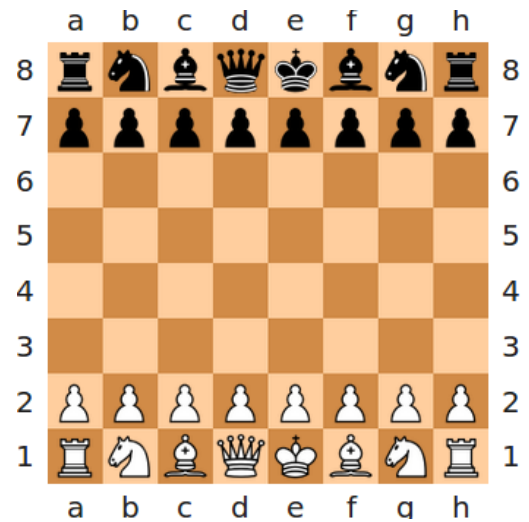
In deterministic environments: for any given action, the next state is known for certain.

In fully observed environments: s_t is a complete view[1] of the environment at time t.

For example, 8-puzzle, Noughts & crosses (tic tac toe), Chess, and many other board games.

1	3	5
7	2	4
8		6

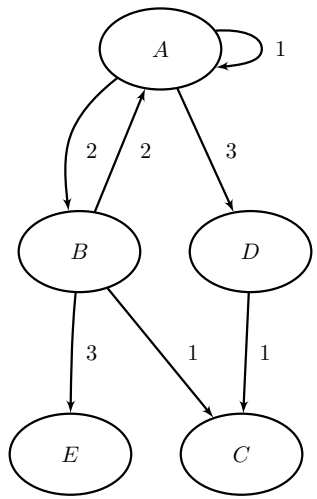
×		○
	○	×
×		○



[1] Otherwise it is a partially-observed environment

Fully Observed Deterministic Environments

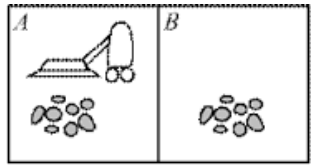
- $\mathcal{S}$ state space (e.g., $\mathcal{S} = \{A, B, C, D, E\}$), $s_t \in \mathcal{S}$
- $\mathcal{A}$ action space (e.g., $\mathcal{A} = \{1, 2, 3\}$), $a_t \in \mathcal{A}$
- r reward function, $r_t = r(s_{t-1}, a_t, s_t)$
  (e.g., $r(D, 1, C) = 1$, $r(B, 3, E) = -1$, and else $r(\cdot, \cdot, \cdot) = 0$); i.e., $r_t \in \{-1, 0, +1\}$



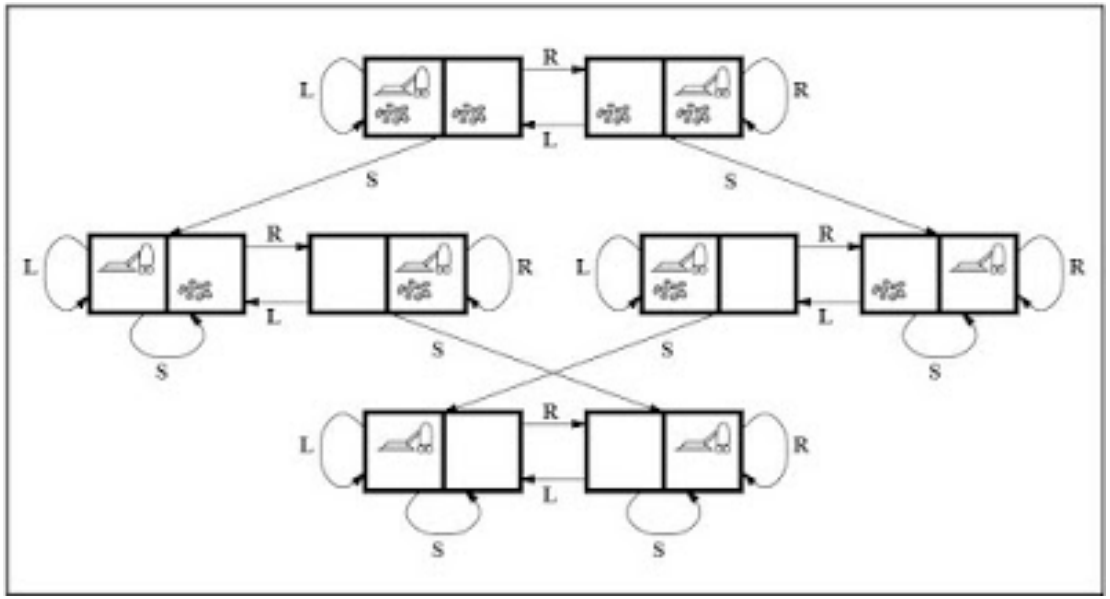
Actions shown on edges.

An epsiode/trace, e.g., $\{A, 0, 1, A, 0, 3, D, 0, 1, C, 1\}$.

For example, Vacuum Cleaner World:

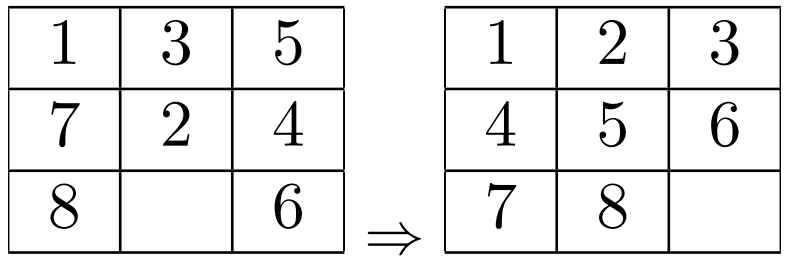


There are 8 possible states:



From Russel and Norvig, *Artificial Intelligence: A Modern Approach (2nd ed.)* 2002

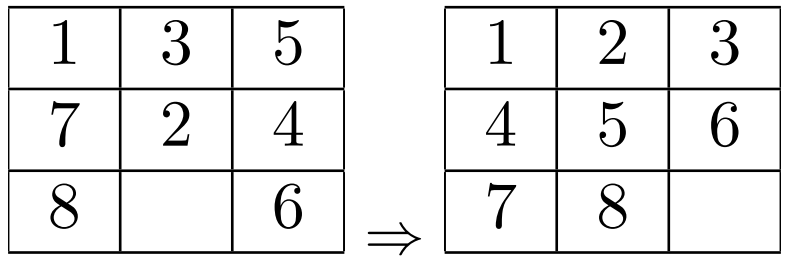
For example, the `8-puzzle`,



It's just a search (each node is a state):

1. Generate the search tree to goal state
2. Apply payoff to leaf
3. Backup
4. Choose the best branch

For example, the `8-puzzle`,



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4. Choose the best branch

What about against an adversary (e.g., tic tac toe)? Can be made deterministic via minimax algorithm.

What if the branching factor is too large and/or long route to goal state (e.g., chess)? Simple search won't work.

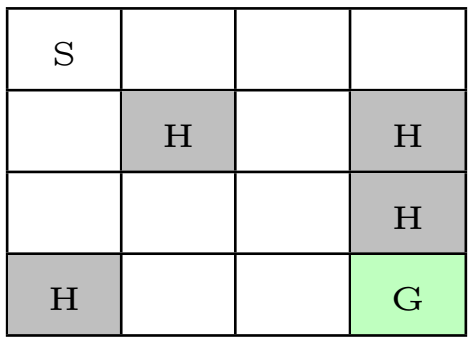
Stochastic Environments and MDPs

Stochastic Environments

In a stochastic environment, the agent takes action a from state s and arrives to state s' *with probability*[2]

$$s_{t+1} \sim p(s'|s, a)$$

The FROZEN LAKE environment: Get from Start state to Goal state without falling through a Hole in the ice. The ice is slippery, e.g., $p([1,1]|[2,1], \text{LEFT}) = 0.33$.



Not a search path from start to goal!

[2] N.B. $p(s'|s, a) \equiv \Pr[S_t = s'|S_t = s, A_t = a]$

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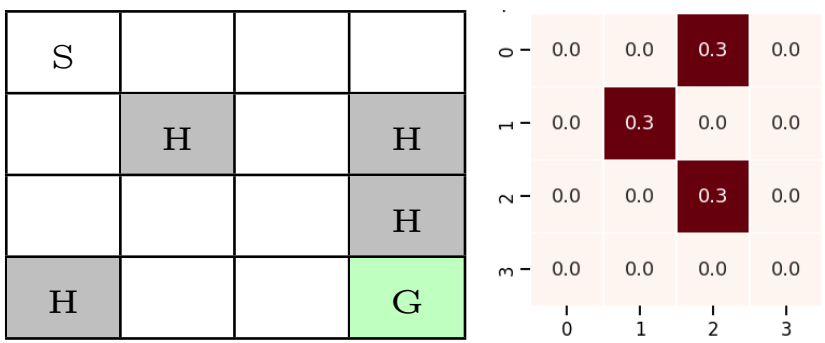


Not a search path from start to goal!

[2] N.B. $p(s'|s, a) \equiv \Pr[S_t = s'|S_t = s, A_t = a]$

A Markov Decision Process (MDP)

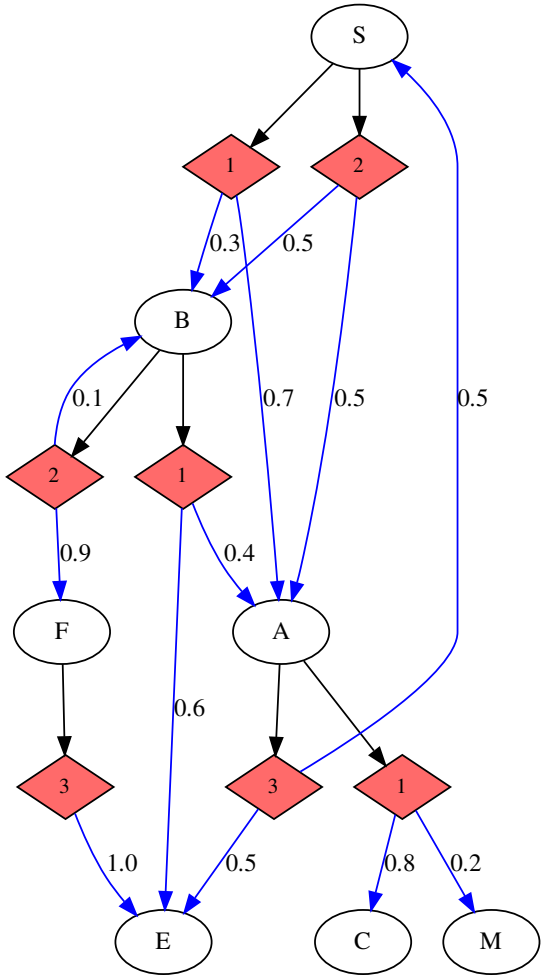
MDP: A model of the environment.

- $\mathcal{S}$ state space (e.g., {S,B,F,A,E,C,M})
- $\mathcal{A}$ action space (e.g., {1,2,3})
- $r(s, a)$ or $r(s, a, s')$ reward function
- $p(s'|s, a)$ transition function

▷ Compactly: $p(s', r \mid s, a)$

We do not necessarily know this model.

Goal: Learn policy π, which takes the best action from any given state.



Action in diamonds, p shown on edges; $r(\mathtt{A}, 1, \mathtt{M}) = 1$ and $r(s_{t-1}, a_t, s_t) = 0$ elsewhere

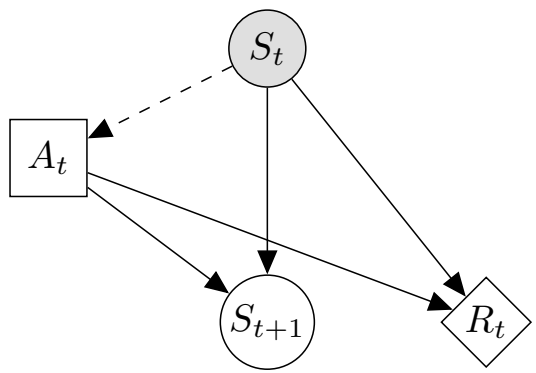
The Markov Property

MDPs provide a framework for modeling sequential decision making in stochastic environments. Most reinforcement learning problems can be framed as an MDP.

- **M** The Markov property
- **D** We add decisions (motivated by rewards)
- **P** A [Markov] process/chain[3]

Markov property: The effects of action a_t from state s_t depend only on those values;

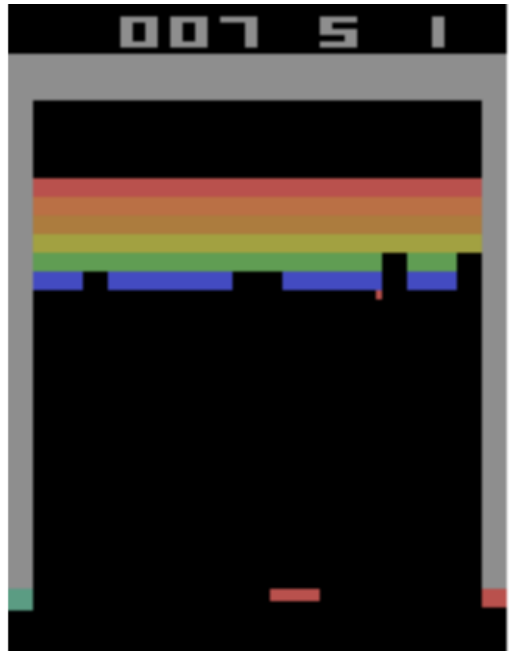
$$p(s_{t+1}|s_t, a_t) = p(s_{t+1}|s_1, \ldots, s_t, a_1, \ldots, a_t)$$



[3] Remark: If $P(s_{t+1}|s_t, a_t) = P(s_{t+1}|s_t)$ we reduce to a Markov chain

Does your environment satisfy the Markov property?

(Can you (an agent) perform optimally from state s_t?)

$s_t =$ 

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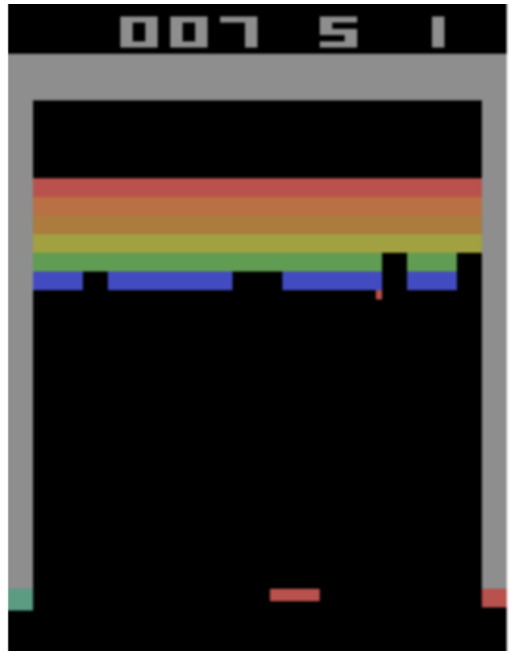
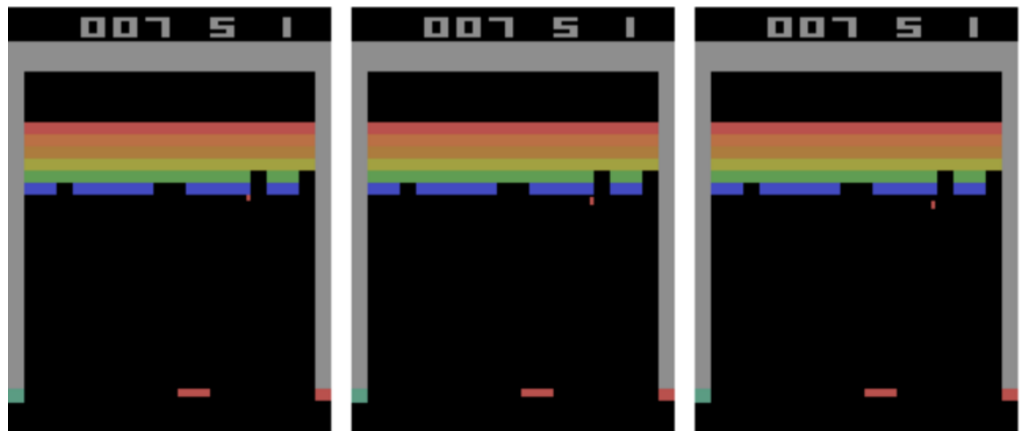
$s_t =$ 

$s_t =$ 

Other solutions: LSTMs, track differences.

Policy, Return/Gain and the Bellman Equations

The Policy

A reminder:

$$a_t = \pi(s_t)$$

(should work for all $s_t \in \mathcal{S}$). But which policy is best?

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The best policy should take the best action from the current state;

$$a_t^* = \pi(s_t)$$

i.e., the action to to optimize . . .

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The best policy should take the best action from the current state;

$$a_t^* = \pi(s_t)$$

i.e., the action to to optimize . . .

major question: **what are we optimizing?**

. . . the reward at the next step (r_{t+1})? *No*, consider –

- what if the reward is only given at the end (r_T)
- what if a_t has nothing to do with r_{t+1}
- $r_{t+1} \sim R_{t+1}$ is a random variable; inherits randomness from the stochastic environment (and a stochastic policy)

The Return/Gain (Finite Scenario)

The return (aka gain) at step t is

$$\begin{aligned} G_t &= \sum_{i=t}^{T} R_i \\ &= R_t + R_{t+1} + R_{t+2} + \ldots + R_T \end{aligned}$$

i.e., the sum of rewards until the end of the episode; it indicates the value at current time t.

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i.e., the sum of rewards until the end of the episode; it indicates the value at current time t.

Considerations:

- What is T? What if $T = \infty$?
- Does it make sense that G_t is the same when $r_{t+1} = 1$ vs when $r_{t+1000} = 1$ (and all others 0)?

The Return/Gain (Infinite Scenario)

The return (aka gain) at step t is

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{k+t+1} \tag{1}$$

$$= R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots \tag{2}$$

for discount factor $\gamma \in (0, 1)$ which indicates the relative value of closer rewards.

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$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{k+t+1} \tag{1}$$

$$= R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots \tag{2}$$

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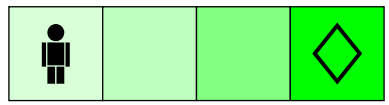


Task: The agent should take actions A_t to maximize G_t!

Problem: G_t is from the future (may be even $t = \infty$)!
G_t inherits the randomness from all $R_{t+1}, R_{t+2}, \dots$

Solution: We should maximize expected return $\mathbb{E}[G_t]$.

The Value Function

The value function (aka state-value function),

$$V^{\pi}(s) = \mathbb{E}[G_t | S_t = s]$$

maps a state to a value.

The value of a state s is the expected return from that state following policy π.

We may think of a vector of $|\mathcal{S}|$ values; if $\mathcal{S} = \{s_1, s_2, s_3, s_4\}$:

	s_1	s_2	s_3	s_4
V				

The policy is implicit: move to states with high value.

A V-function and Policy for the Frozen Lake Environment:

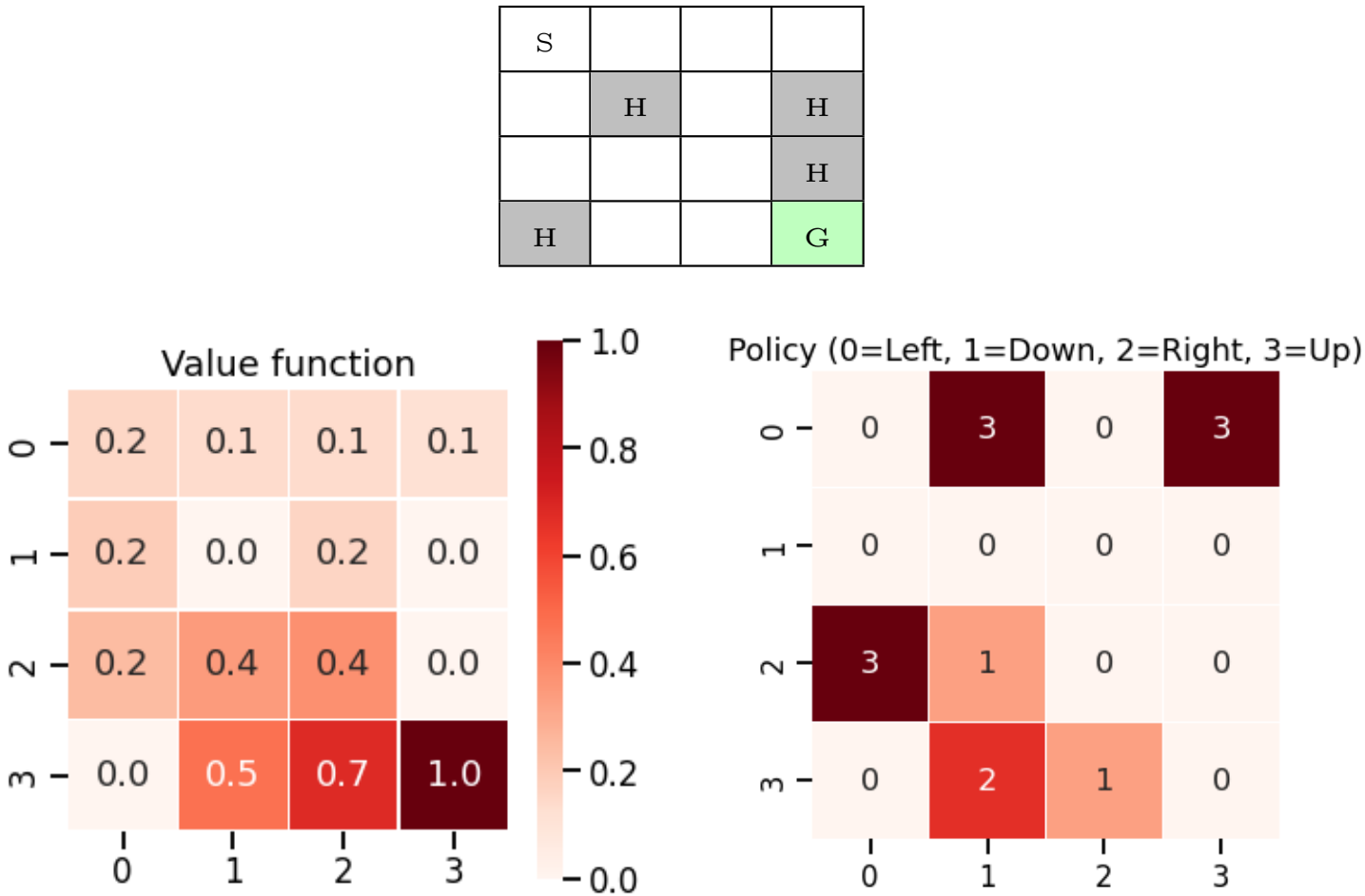


Image credits: Jérémie DeCock (TD teacher)

The Action-Value Function

The action-value function,

$$Q^{\pi}(s, a) = \mathbb{E}[G_t | S_t = s, A_t = a]$$

maps a state *and action* to a value.

We may think of a table of $|\mathcal{S}| \times |\mathcal{A}|$ values; with $\mathcal{A} = \{a_1, a_2\}$:

Q	a_1	a_2
s_1		
s_2		
s_3		
s_4		

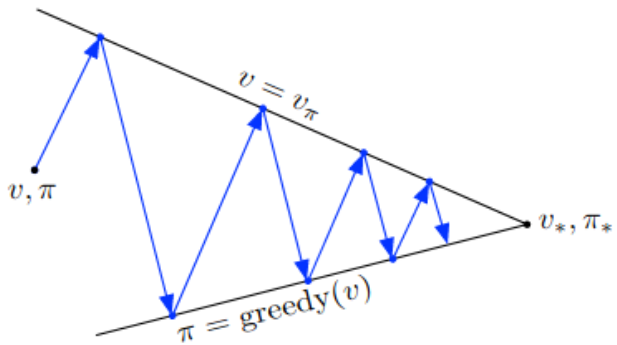
The greedy policy is explicit:

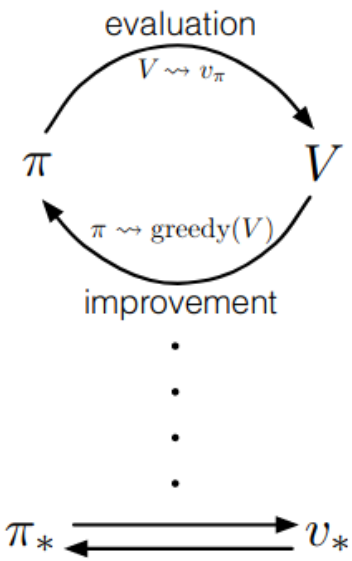
$$a_t = \pi(s_t) = \underset{a \in \mathcal{A}}{\text{argmax}}\, Q(s_t, a)$$

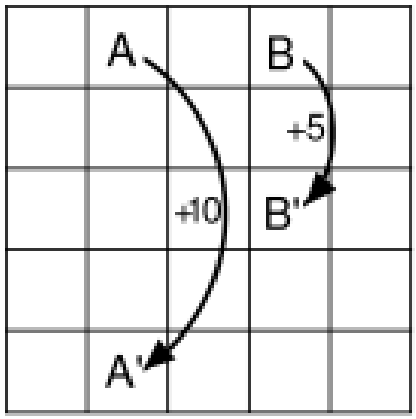
Bellman Optimality Equation

$$
\begin{aligned}
V^*(s) &= \max_{a \in \mathcal{A}(s)} Q^{\pi_*}(s, a) \\
&= \ldots \quad \triangleright \text{ See } \textit{Sutton and Barto, 2018} \text{ for derivation} \\
&= \max_{a \in \mathcal{A}(s)} \sum_{s' \in \mathcal{S}, r \in \mathcal{R}} p(s', r | s, a) \left[r + \gamma V^*(s') \right] \\
\pi^*(s) &= \operatorname*{argmax}_{a \in \mathcal{A}(s)} Q^{\pi_*}(s, a)
\end{aligned}
$$

Note the max and the argmax; relationship between π^* and V^*.



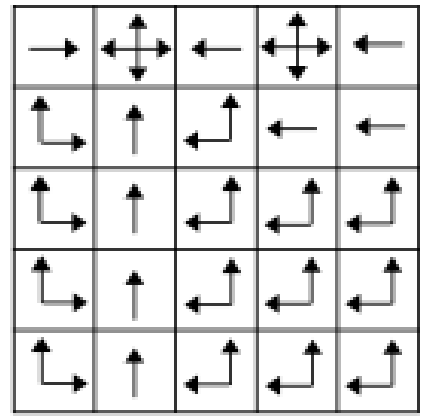




a) gridworld

22.0	24.4	22.0	19.4	17.5
19.8	22.0	19.8	17.8	16.0
17.8	19.8	17.8	16.0	14.4
16.0	17.8	16.0	14.4	13.0
14.4	16.0	14.4	13.0	11.7

b) V^*



c) π^*

Ref: Sutton and Barto. *Reinforcement Learning: An Introduction*, 2018.

In reinforcement learning, we do not know the underlying system dynamics of the MDP, we need to learn it through interaction with the environment.

Bellman Equation for V^π (Preliminaries)

Recall (Slide 31) the value function:

$$V^\pi(s) = \mathbb{E}[G_t | S_t = s] \tag{3}$$

A recursion trick we will need:

$$\begin{aligned} G_t &= R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \gamma^3 R_{t+4} + \cdots \\ &= R_{t+1} + \gamma(R_{t+2} + \gamma R_{t+3} + \gamma^2 R_{t+4} + \cdots) \\ &= R_{t+1} + \gamma G_{t+1} \quad \triangleright \text{ Recursion!} \end{aligned} \tag{4}$$

A reminder on conditiontal probability and expectations and marginalizing out (some function g):

$$\mathbb{E}_{A,R,S'}[g(A, R, S') | S = s] = \sum_{a,r,s'} g(a, r, s') P(a, r, s' | s)$$

Total law of expectation:

$$\mathbb{E}[G] = \mathbb{E}_S[\mathbb{E}[G|S]]$$

Bellman Equation V^π (Derivation)

From an MDP $(\mathcal{S}, \mathcal{A}, \mathcal{R}, p, \gamma)$:

$$
\begin{aligned}
V^\pi(s) &= \mathbb{E}_\pi \left[G_t | S_t = s \right] \quad \triangleright \text{ Cond. expectation; from Eq. (3)} \qquad (5) \\
&= \mathbb{E}_\pi \left[R_{t+1} + \gamma G_{t+1} \middle| S_t = s \right] \quad \triangleright \text{ Recursion; from Eq. (4)} \\
&= \sum_{a,s',r} \underbrace{p(a|s)p(r|s,a)p(s'|s,a)}_{p(a,r,s'|s)} \left[r + \gamma \mathbb{E}_\pi \left[G_{t+1} | S_{t+1} = s' \right] \right] \\
&= \sum_{a \in \mathcal{A}} \pi(a|s) \sum_{s' \in \mathcal{S}, r \in \mathcal{R}} p(r, s'|s, a) \left[r + \gamma \mathbb{E}_\pi \left[G_{t+1} | S_{t+1} = s' \right] \right] \\
&= \sum_{a \in \mathcal{A}} \pi(a|s) \sum_{s' \in \mathcal{S}, r \in \mathcal{R}} p(r, s'|s, a) \left[r + \gamma V_\pi(s') \right] \quad \forall s \in \mathcal{S} \qquad (6)
\end{aligned}
$$

Where the final line completes the recursion via Eq. (5).

Bellman Equation V^π (Derivation)

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\end{aligned}
$$

Where the final line completes the recursion via Eq. (5).

Why is this important? It's the MDP + recursion! (the 'solution'!)
We just need V^* ...

Bellman Optimality Equation V^*

The optimal policy is

$$\pi^* = \text{argmax}_{\pi} V^{\pi}(s) \quad \forall s \in \mathcal{S}$$

The value function associated with this policy is:

$$V^*(s) = \text{max}_{\pi} V^{\pi}(s) \quad \forall s \in \mathcal{S}$$

Note that (the value from state s, under policy π)

$$V^{\pi}(s) = Q^{\pi}(s, \pi(s))$$

It means that (from Eq. (6)):

$$Q^{\pi}(s, \pi(s)) = \sum_{s' \in \mathcal{S}, r \in \mathcal{R}} p(r, s'|s, a) \left[r + \gamma V_{\pi}(s') \right] \qquad \forall s \in \mathcal{S}$$

The action-value function Q shares the same optimal policy.

Bellman Optimality Equation

$$
\begin{aligned}
V^*(s) &= \max_{a \in \mathcal{A}(s)} Q^{\pi_*}(s, a) \\
&= \dots \\
&= \max_{a \in \mathcal{A}(s)} \sum_{s' \in \mathcal{S}, r \in \mathcal{R}} p(s', r | s, a) \left[r + \gamma V^*(s') \right] \\
\pi^*(s) &= \operatorname*{argmax}_{a \in \mathcal{A}(s)} Q^{\pi_*}(s, a)
\end{aligned}
$$

(again the max and the argmax – back to Slide 38).

Bellman Optimality Equation

$$
\begin{aligned}
V^*(s) &= \max_{a \in \mathcal{A}(s)} Q^{\pi_*}(s,a) \\
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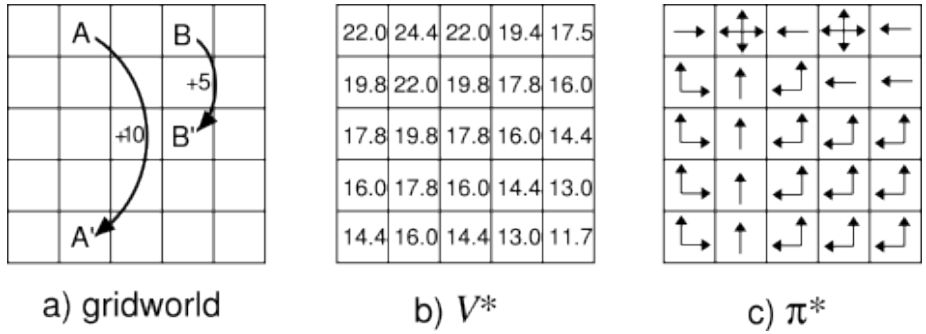
\pi^*(s) &= \operatorname*{argmax}_{a \in \mathcal{A}(s)} Q^{\pi_*}(s,a)
\end{aligned}
$$

(again the max and the argmax – back to Slide 38).

So, initial and final question: how to get π^*?

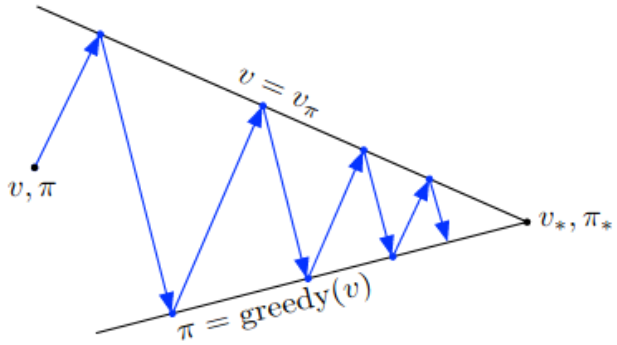


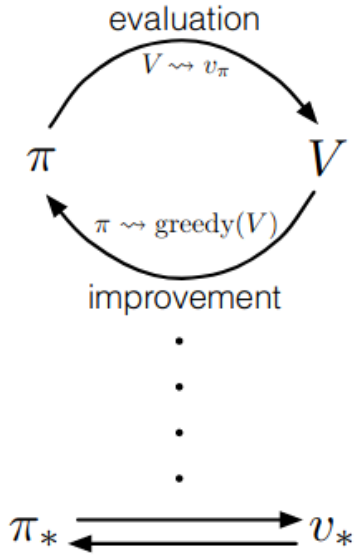
Ref: Sutton and Barto. *Reinforcement Learning: An Introduction*, 2018.

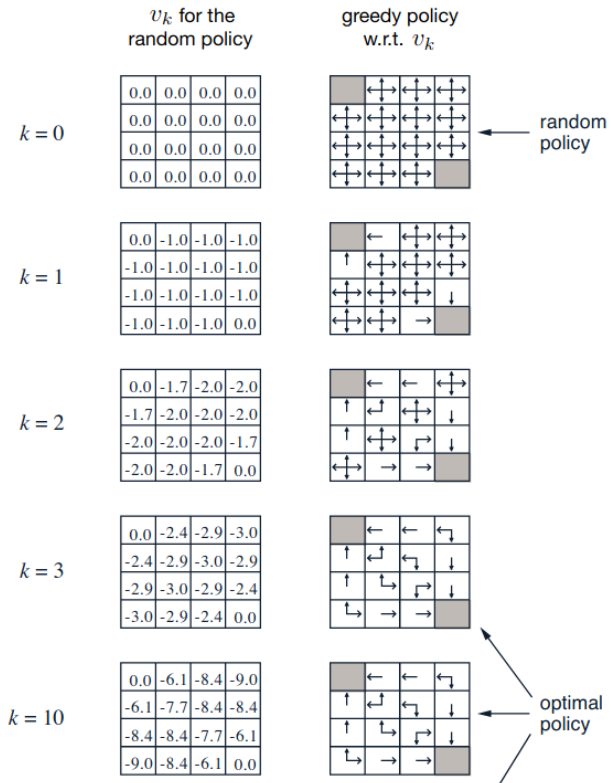
Iterative solutions:

- Value iteration
- Policy iteration
- Q-learning
- Sarsa
- ...

In reinforcement learning, we do not know the underlying system dynamics of the MDP, we need to learn it through interaction with the environment (but we can learn it).


$v = v_\pi$
v, π
v_*, π_*
$\pi = \text{greedy}(v)$


evaluation
$V \rightsquigarrow v_\pi$
π
V
$\pi \rightsquigarrow \text{greedy}(V)$
improvement
π_*
v_*


v_k for the random policy
greedy policy w.r.t. v_k
$k = 0$
$k = 1$
$k = 2$
$k = 3$
$k = 10$
random policy
optimal policy

Exploration vs Exploitation

We need to learn the system dynamics through interaction.

One possibility: Use a behaviour policy (possibly random) μ:

$$a_t \sim \mu$$

(this is an off-policy method).

1. Play many episodes with policy μ; record G_t for each (s_t, a_t)
2. Use these samples to approximate the expectation:

$$Q^{\mu}(s, a) = \frac{1}{n} \sum_{i=1}^{n} G_t^{(i)} \approx \mathbb{E}[G_t | s, a]$$

3. Employ the greedy policy π on Q.

Trade-off: Exploration vs exploitation.

This in Monte Carlo RL. More on Monte Carlo next time!

Types of Reinforcement Learning Agents

Value-Based or Policy-Based ?

- Value Based (value function; policy is implicit)
- Policy Based (no value function)
- Actor Critic (both value function + policy)

Model Free vs Model Based: We can build a model of the environment, or do without it.

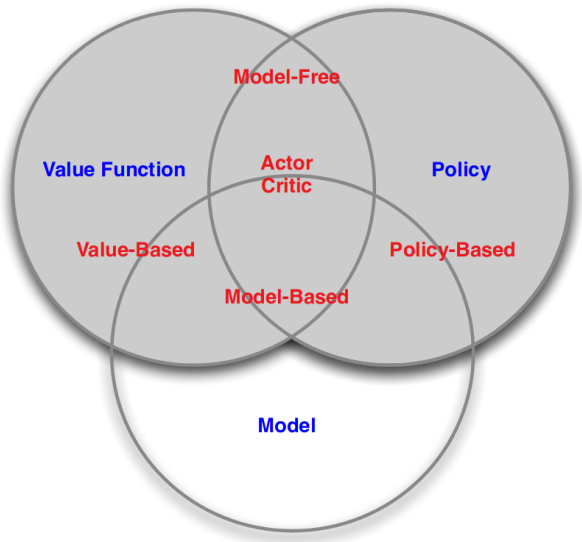


Image from [1]

Summary / Important Concepts

- Agent and Environment
- States, Actions, Reward
- Model of the environment (MDP)
  - Markov property
  - Deterministic vs stochastic
  - Unknown vs fully observable vs partially observable
- Return/Gain (finite horizon vs infinite horizon; γ)
- Policy (deterministic policy, stochastic policy, greedy policy)
- State Value and Action-Value functions
- Bellman Equations
- Exploration vs Exploitation trade-off

Reinforcement learning is difficult (compared to supervised learning), but there are many applications where supervised learning does not apply.

Deep Reinforcement Learning

[2]

Game mechanics still relatively simply (move, left, right, shoot, . . .), but state space is huge! Q-table impossible!

A Deep Representation of the Q-table

We replace the Q table with a neural network:

$$Q(s, a) = q_{\boldsymbol{w}}(s)_a$$

where $q_{\boldsymbol{w}}$ is a (deep) neural network parametrized by $\boldsymbol{w}$.

For example,

$$[Q(s, a_1), \ldots, Q(s, a_4)] = q_{\boldsymbol{w}}(s)$$

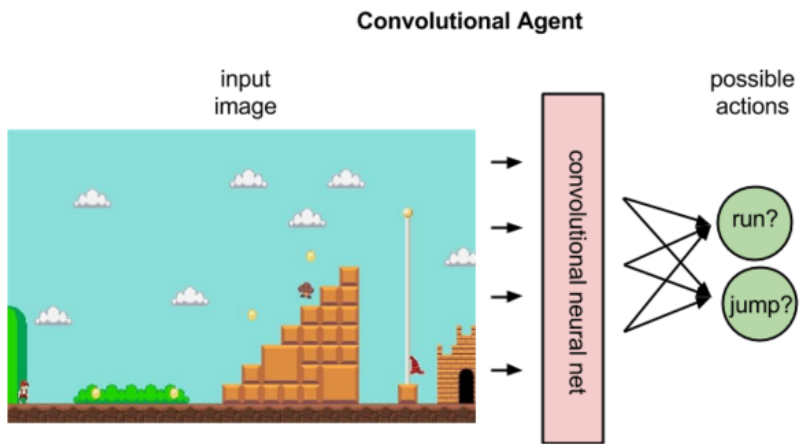
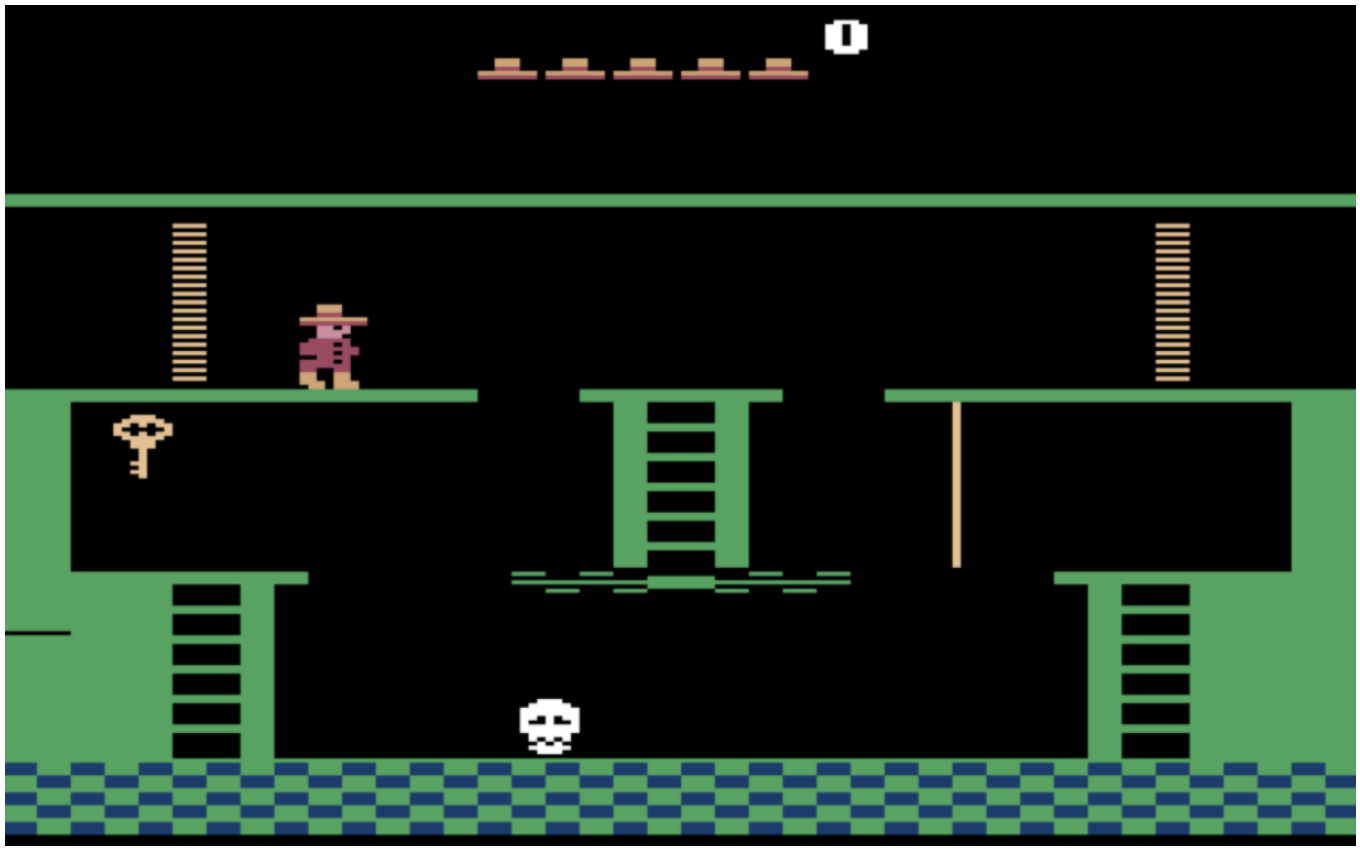


Image Source: [3]

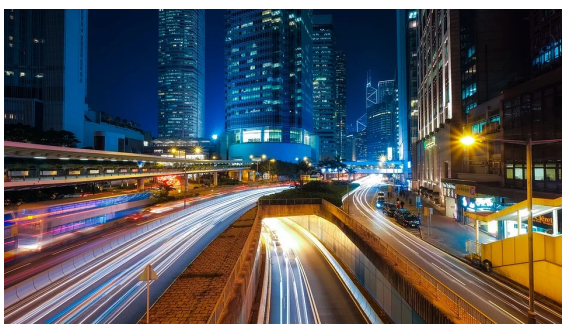
Montezuma's Revenge (much harder than FPS!)



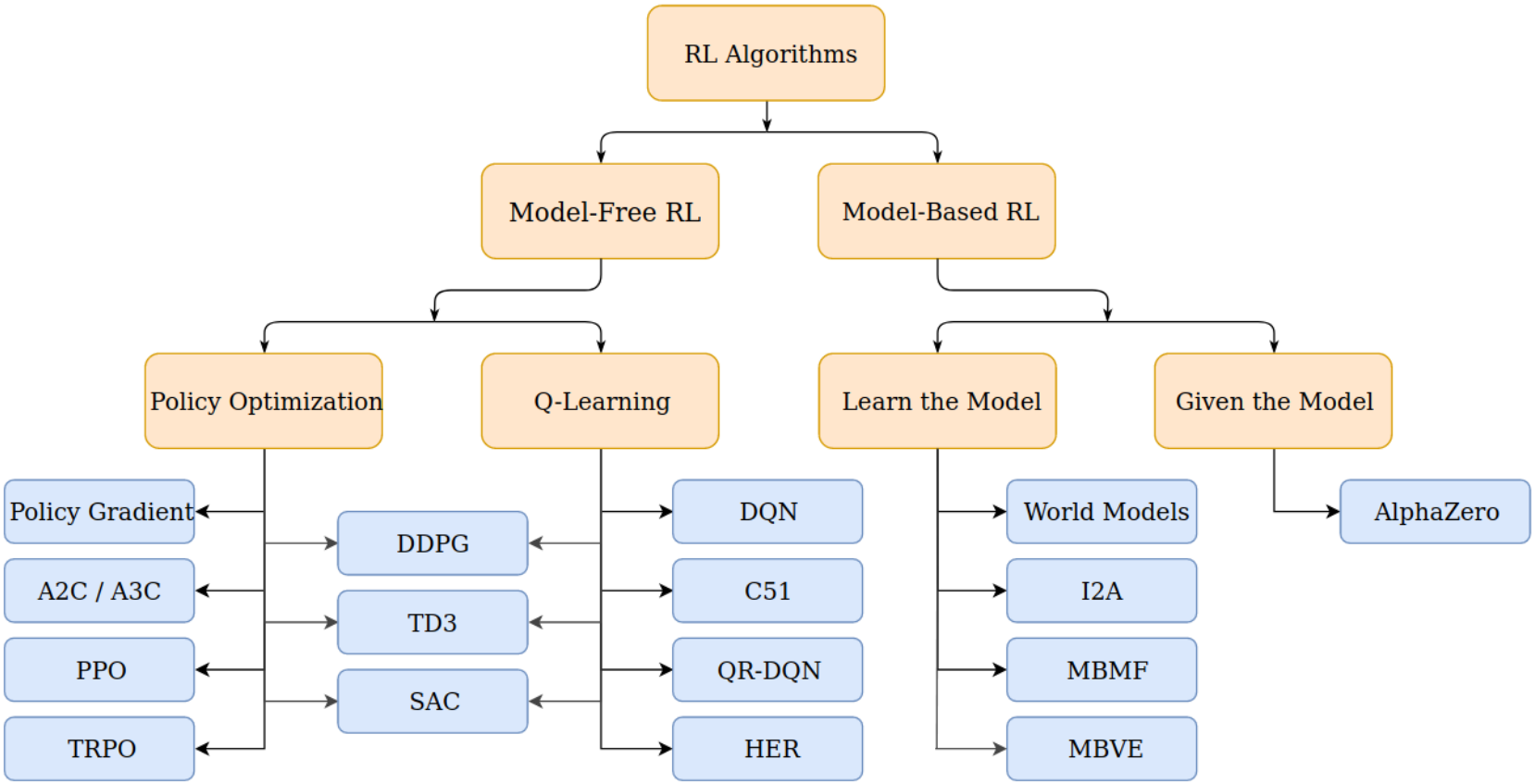
Montezuma's Revenge – Notoriously Difficult for RL Agents [4]

Modern Challenges

- Learning quickly with limited samples
- Safety issues
- Explainable agents, interpretable actions
- Multi-objective reward fns, multi-agent
- Real-time learning and inference
- Delayed/partial/weak observations



A Taxonomy of Methods



Modern Machine Learning Methods [5]

Reinforcement Learning I

INF581 Advanced Machine Learning and Autonomous Agents

Jesse Read